DOCUMENT RESUME

ED 441 704 SE 063 828

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TITLE Conceptual Change and Chemistry Achievement: A Two-Dimensional Model.
PUB DATE 2000-04-00
NOTE 54p.; Paper presented at the Annual Meeting of the American Educational Research Association (New Orleans, LA, April 24-28, 2000).
PUB TYPE Reports - Research (143) -- Speeches/Meeting Papers (150)
EDRS PRICE MF01/PC03 Plus Postage.
DESCRIPTORS Achievement; Algorithms; Chemistry; College Students; *Concept Formation; *Critical Thinking; *Epistemology; Higher Education; *Learning; Metacognition; Multiple Choice Tests; Regression (Statistics); *Science Education; Thinking Skills
IDENTIFIERS Guttman Scales; Predictive Discriminant Analysis

ABSTRACT

The results of this study are consistent with a two-stage model of learning chemistry, a multi-dimensional subject, in which students accumulate knowledge in stage one, and then restructure their knowledge in stage two. When cognitive, metacognitive and achievement variables were subjected to a predictive discriminant analysis (PDA) procedure, three qualitatively distinct achievement groups emerged. The rote learners were apparently stuck in stage one. Conversely, stage two began with a fork in the achievement pathway. Some learners, 'algorithm memorizers,' took the "low road" apparently because they sought and used memorized algorithms--a form of weak restructuring or tuning. Conversely, other learners, 'conceptualizers,' took the "high road" because they tended to possess a coherent set of attributes that allowed them to create new knowledge structures--a form of strong restructuring. Analysis of writing journals revealed different perceptions among the three groups. Also, two extra exam question sets on conceptual knowledge redefined group membership for some students. Overall, this study provides an empirical model--a graphical achievement method--that could serve as a methodological bridge between student achievement characteristics and domain-specific conceptual change models (DS-CCM). Based on these results, several suggestions are made for further research studies and effective instructional interventions. (Contains 84 references.) (Author/YDS)

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Conceptual Change and Chemistry Achievement: A Two-Dimensional Model

ED 441 704

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Paper presented at the 81st Annual Meeting of the American Educational Research Association, New Orleans, 24-28 April 2000.

Abstract

The results of this study are consistent with a two-stage model of learning chemistry, a multi-dimensional subject, in which students accumulate knowledge in stage one, and then restructure their knowledge in stage two. When cognitive, metacognitive and achievement variables were subjected to a predictive discriminant analysis (PDA) procedure, three qualitatively distinct achievement groups emerged. The *rote learners* were apparently stuck in stage one. Conversely, stage two began with a fork in the achievement pathway. Some learners, "*algorithm memorizers*," took the "low road" apparently because they sought and used memorized algorithms-- a form of weak restructuring or tuning. Conversely, other learners, "*conceptualizers*," took the "high road" because they tended to possess a coherent set of attributes that allowed them to create new knowledge structures-- a form of strong restructuring. Analysis of writing journals revealed different perceptions among the three groups. Also, two extra exam question sets on conceptual knowledge redefined group membership for some students. Overall, this study provides an empirical model-- a graphical achievement method-- that could serve as a methodological bridge between student achievement characteristics and *domain-specific conceptual change models* (DS-CCM). Based on these results several suggestions are made for further research studies and effective instructional interventions.

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THEORETICAL FRAMEWORK

Over the last two decades of research in science education, the theoretical model of conceptual change has been one of four paradigms (Eylon & Linn, 1988) that have described the nature of student learning in science classrooms. If students are to understand science, then they must already possess conceptual knowledge that organizes information into a coherent set of interrelated concepts, associated facts, and links among these components. A conceptual change in their knowledge structures is needed so they can acquire new knowledge in a meaningful way; otherwise, they may be limited to rote learning of new material (Pearsall, Skipper, & Mintzes, 1997).

Rumelhart and Norman (1978) incorporated both types of learning in their model of learning that begins with accretion, i.e., accumulation of knowledge primarily via memorization, and then proceeds to the tuning of conceptual structures (weak restructuring) or the creation of new knowledge structures (strong restructuring). Treagust et al. (Tyson, Venville, Harrison, & Treagust, 1997) have described three "boundary conditions" that serve as essential factors that must be engaged so that a change from one conceptual knowledge structure to another can occur. That is, conceptual change requires that the learners possess the appropriate epistemological and ontological commitments in order to truly understand science. This drive to understand must occur within a particular social context that depends both upon learners' affective and cognitive states (Pintrich, Marx, & Boyle, 1993). Thus, science instruction should supply all of the critical conditions needed to support this deeper, more meaningful way of learning science (Salomon & Perkins, 1998).

Objectives

In this paper the author presents an empirical model of chemistry achievement that is designed to bridge the gap between conceptual change models and the set of student responses that a teacher gets when a multiple-choice examination is used to assess achievement. This empirical method transformed student responses on a test into qualitatively distinct achievement categories that were plotted on a two-dimensional graph. The author used predictive discriminate analysis (PDA) to characterize each of these categories and to predict which students belonged to each one. Analysis of students' journal-writing was used to check for their perceptions that should correlate with the results of the PDA. In the final section, the relationships among the results of this study, an eclectic model of conceptual change, and instructional interventions were discussed.

Chemistry: A Multi-Dimensional Subject

Throughout most of the twentieth century, achievement in American schools, colleges, and universities was measured in a unidimensional manner based on the underlying principles of behavioral psychology and the standard test theory (e.g., IQ test theory). These principles assume that each area of study, e.g. general chemistry, possesses a single factor that determines how well a student will perform in it (Mislevy, 1996; Masters & Mislevy, 1993). In other words, a unidimensional scale uses a single score (the total score or % correct) to represent a student's performance on a test (Goldstein, 1996). Although this is the normal method teachers use to assign grades to students, the method assumes that all learners only accumulate knowledge within a particular subject (Goldstein, 1996). This idea is consistent with the principles of behavioral psychology but not with those of cognitive psychology (Alexander, 2000; Mislevy, 1996; Masters & Mislevy, 1993).

Although most chemistry instructors usually assign grades on a unidimensional basis for each test or assignment given, learning chemistry is a complex process. Chemistry has a multidimensional structure (deVos et al., 1994; Jensen, 1998) that requires a set of multidimensional skills (Bowen & Phelps, 1997; Bunce, 1993; Coppola et al., 1997; Lockie & van Lanen, 1994):

- memorization and comprehension of chemical terminology,
- algorithmization of chemical processes and mathematical relationships,
- manipulation of laboratory materials and equipment, and
- integration of these component skills to yield an understanding of both chemical principles and phenomena.

Thus, if subject matter knowledge and conceptual change are to be studied in this domain, then an achievement measure should provide at least a two-dimensional analysis of learning.

Two Types of Understanding in Chemistry

Algorithmic Understanding. There are two stages of algorithmic understanding: in stage one, students usually memorize a "standard algorithm" to solve a particular set of problems (Bodner, 1987; Bodner & McMillen, 1986), then in stage two, they can generate their own algorithm, an "invented algorithm," in order to solve a wider range of problems (Fennema et al., 1998; Middlecamp & Kean, 1987). In the first stage, a standard algorithm can be useful because it provides a "step by step" procedure to solve a particular kind of problem. Thus, students are learning a routine and automatic procedure rather than struggling to understand the problem (Bodner, 1987; Bodner & McMillen, 1986; Lythcott, 1990). However, a standard algorithm tends to reduce a real problem, which requires critical thinking skills (Rojas de Astudillo & Niaz, 1996; Zoller, 1993), to an exercise, which does not require any of these skills (Bodner, 1987; Bodner & McMillen, 1986; Lythcott, 1990).

Conversely, in stage two of algorithmic understanding, students must derive their own algorithms to solve more complex problems (Lythcott, 1990; Middlecamp & Kean, 1987). An "invented algorithm" is more demanding than a standard algorithm because it

- uses a reasoning strategy that combines concepts and algorithms in a problem (Middlecamp & Kean, 1987; Rojas de Astudillo & Niaz, 1996), and
- requires a true understanding of the underlying structure of the subject matter (Lythcott, 1990; Fennema et al., 1998).

In most cases, students only begin to use this second stage of algorithmic understanding after a second or third exposure to the same material (Fennema et al., 1998). For example, in high school chemistry, if students learn to use a standard algorithm to solve gram-to-gram stoichiometric problems, then in general chemistry they are capable of extending this algorithm without help to include a wider range of problems (Finkel, 1996; Middlecamp & Kean, 1987), e.g. molar-to-molar, liters(gas)-to-grams, etc.

Conceptual Understanding. A familiar problem can be easily solved with the appropriate algorithm, but an unfamiliar problem requires the use of a more sophisticated solution strategy (Middlecamp & Kean, 1987; Niaz, 1995). A conceptual problem is frequently "unfamiliar" because its solution requires a multi-step search for meaning (Lythcott, 1990). This search uses a set of models (reasoning strategies that use concepts) to forge a conceptual understanding (Niaz, 1995; Lee et al., 1996; Rojas de Astudillo & Niaz, 1996). To acquire this understanding, learners must:

- understand all three levels of representation for chemical principles (see below),
- be able to use "invented algorithms" (see above), and
- develop their conceptual knowledge.

These three factors are part of the underlying logical structure of chemistry (Jensen, 1998; deVos et al., 1994).

The chemical concepts and principles that are the most difficult for learners are those that involve the three levels at which chemistry can be taught and understood (Bowen & Phelps, 1997; Gabel, 1993; Johnstone, 1983; Johnstone & El-Banna, 1986):

1) the symbolic level (chemical formulas, equations, and mathematical relationships);
2) the particulate level (sketches of atoms, molecules and ions, e.g., o and • for different atoms/elements); and
3) the macroscopic level (observable chemical processes in the laboratory).

Problems at the particulate level (see subsection, *Assessment of Conceptual Understanding*) are the best indicators of conceptual understanding and the most difficult ones for students (Gabel, 1993). This difficulty is amplified when chemistry lectures focus almost exclusively on the symbolic level (Gabel, 1993), while laboratory work features observations of chemical phenomena. To overcome this difficulty,

students need instructional help to learn to visualize chemical phenomena and principles at all three levels (Gabel & Bunce, 1994). Once they can visualize, they can begin to see connections among the three levels (Bowen & Phelps, 1997; Gabel, 1993) and thus to develop a conceptual understand of chemistry.

The Interaction between Algorithmic and Conceptual Understanding. Many chemical educators have found a clear dichotomy in which algorithmic problems are usually easier, and conceptual problems are more difficult (Nurrenbern & Pickering, 1987). On the other hand, Niaz (1995) has provided evidence that this apparent dichotomy is actually a continuum of student models: A student's first model usually focuses upon memorizing and using algorithms, and then shifts to subsequent models that facilitate successively greater degrees of conceptual understanding. Nakhleh and Mitchell (1993) have categorized different student models into four quadrants based on their scores on two orthogonal dimensions: low or high algorithmic versus low or high conceptual problem-solving abilities.

The Conceptualizer Label. In this study, the label 'conceptualizer' is used to represent those students who "should" be able to conceptualize the material. The extent to which this label actually represents students who are performing the implied mental process is unknown, but this should be the topic for an entire 'fleet' of research agendas. In this study, the ability to conceptualize is defined in a manner similar to the definition given by Zuzousky and Tamir (1999): "... to deduce scientific principles and use them to solve problems and construct scientific explanations, which is at the heart of science inquiry...(p. 1118)." These authors contend that change in 'ability to conceptualize' depends upon "the existence of prior knowledge and with the ability to build upon this knowledge in generating scientific explanations (p. 1118)." Also, Clancey (1997) contributes to this definition by stating that, "In people, nonverbal conceptualization can organize the search for new ideas (p. 249)." Also, he adds that "What is conceptualizing if not manipulating stored descriptions (p. 278)? [Capitalization removed from the original quote.]" Ultimately, the ability to conceptualize within a given domain may be dependent upon 'moderately abstract conceptual representation(s)' (MACR) that help the novice/expert (Zeitz, 1997) become "facile at processing information at the appropriate level of abstraction for that domain (p. 44)." The level of MACR's "has been demonstrated to be an effective basis for introducing novices to a domain (p. 62)." Thus, it is hoped that the reader now feels comfortable with the rationale' for the use of this 'elite term' in an educational research context such as the study reported in this paper.

Achievement Measures

Multiple-choice Tests and Achievement

For many decades multiple-choice examinations have been criticized for overemphasizing knowledge of detail at the expense of true understanding (Hinckley & Lagowski, 1966; Kogut, 1996;

Wright et al., 1998; Zoller, 1993). Despite its limitations, researchers have demonstrated that this exam format can be designed to include both algorithmic and conceptual problems (Sadler, 1998). This design is most effective when a test includes a flexible grading format (Hinckley & Lagowski, 1966) and a relatively wide range of difficulty levels, i.e., some easy items, some moderate, and a few difficult items. Thus, most students could be challenged to use their knowledge and skills on the test up to some particular difficulty level (Friel & Johnstone, 1988).

Conversely, most standardized multiple-choice tests and some teacher-made chemistry tests are designed to exclude any test item that does not possess a difficulty level in the narrow range around 0.60; i.e., 60% of the students answer the question correctly. The advantage of this test-preparing strategy is that these moderately difficult questions optimize item discrimination, i.e., it spreads out the distribution of scores. Another consequence of this strategy is that it produces a normal distribution of scores, which is illustrated by a bell-shaped curve. The disadvantage of this method is its inherent assumption that learning chemistry is a unidimensional process that limits its cognitive range (Martinez, 1999) possible to where only one factor determines achievement (Wilson, 1996). If a chemistry examination includes two distinctly different types of problems (Goldstein, 1996), e.g., conceptual and algorithmic problems, then an abnormal distribution may be more likely to occur because two different kinds of achievement are being measured. In order to overcome this difficulty, we have used a graphical method (see the Method Section) that transforms a multiple-choice examination into two dimensions of chemistry achievement.

Two Dimensions of Chemistry Achievement. Algorithmic and conceptual understanding, as described above, can be used to construct a model of chemistry achievement that consists of two orthogonal dimensions (Goldstein, 1996). However, algorithmic understanding can be trivial or challenging depending upon the complexity (Johnstone, 1997) of the operations involved (see Table 1). Likewise, conceptual understanding-- although it is inherently more difficult and less familiar --can either require the execution of simple operations or a set of complex operations. Therefore, the algorithmic/conceptual problem types and the two problem-solving parameters interact with each other as shown in Table 1) to produce two achievement dimensions:

- the *knowledge accumulation* dimension (KAcc) consists of problems that are more familiar to students because they require simpler operations, i.e., fewer steps to solve the problem (Johnstone, 1997; Johnstone & El-Banna, 1986). This type of knowledge accumulates (Weinstein & Meyer, 1991) when students take notes during lectures, read the textbook, work the assigned homework problems, and study for examinations.
- the *knowledge construction* dimension (KCon) contains problems which are more difficult because either the content is less familiar or the problem is more complex, i.e., it requires more steps or a more complex set of procedural steps to solve it . This type of knowledge is generated when the

student constructs a reasoning strategy for a partially familiar or complex problem during the problem-solving task (Lythcott, 1990; Niaz, 1995; Rojas de Astudillo & Niaz, 1996; Lee et al., 1996). Overall, there is a tendency for algorithmic problems to predominate in the KAcc dimension, and conceptual problems to be found in the KCon dimension.

METHOD

In this section the author describe a graphical method (Table 2) that uses student performance on a multiple-choice achievement test to generate a two-dimensional graph (Figure 1). This study uses both quantitative and qualitative methods, see below, to describe the different learner characteristics that surface when this method is used.

Participants. The sample for this study consisted of college students enrolled in six lecture sections of first semester general chemistry for science and engineering majors at a medium-sized state university in the south (USA). The three course instructors used primarily traditional teaching methods, and they covered most of the topics included in 12 chapters of a general chemistry textbook (Brown, LeMay, & Bursten, 7th ed., 1997). About 300 students initially enrolled in the course, but 153 students completed the course and only 103 participated in all phases of the study. During the first week of the semester, they took a 20-question chemistry pre-test (CPT) that measured their basic chemistry knowledge and then a 20-question State Metacognitive Inventory, SMI (O'Neil & Abedi, 1996), that queried their awareness of their thinking processes during the CPT. They took four hour-examinations and a comprehensive final examination, which was the test used in this study. A subsample of 62 participants who were enrolled in two sections taught by the author completed two journal-writing assignments in which they expressed their cognitive and affective perceptions regarding the course material that they had learned (McCrindle & Christensen, 1995).

The Graphical Achievement Method. This method was developed from the Guttman scale (Guttman, 1944), which has been modified to account for mastery levels (Schulz, Kolen, & Nicewander, 1997) and knowledge structures (Doignon & Falmagne, 1999). The method transforms data taken from a multiple-choice examination into a two-dimensional achievement model (see Table 3). In steps 1 and 2 of Table 3, the data are entered and organized on a spreadsheet, then in step 3 the test is divided into two subtests at the midpoint of difficulty, i.e., the item with the median difficulty level, so that each subtest has the same number of items. The KCon mean, see last subsection under Achievement Measures, is calculated for each set of students scoring the same number of correct items on the easier KAcc subtest. In step 4 the students are regrouped into their achievement quadrants as described below.

Labels for Achievement Groups. What criteria should be used to determine if an individual student is successful on each subtest (dimension)? For the KAcc subtest, if students score above the class mean for this easier subtest, then they are "successful" on this achievement dimension. Success on the more difficult KCon subtest is relative to a student's KAcc score. In other words, the efficiency of transfer from KAcc to KCon is best represented as the student's KCon to KAcc ratio of scores. Thus, we use this ratio, R_X, to indicate "transfer efficiency." A successful student should have a ratio that is higher than the ratio of means. This class ratio of means is as follows: R_M = KCon mean / KAcc mean.

The two criteria discussed in the above paragraph interact with each other to produce four quadrants (Table 3) that represent four achievement groups, which are described in the Results Section. Students are then classified into four groups, G1 to G4, based on their subtest scores:

- G1a: *rote memorizers* scored below the class KAcc mean, and their $R_X < R_M$;
- G1b: *globalizers* scored below the class KAcc mean, but their $R_X \geq R_M$;
- G3: *algorithm memorizers* score above the class KAcc mean, but their $R_X < R_M$;;
- G4: *conceptualizers* score above the class KAcc mean, and their $R_X \geq R_M$.

This classification scheme is similar to the one developed by Mayer (1987) that classifies learners based on their ability to retain and transfer knowledge within a given domain. He describes 'nonlearners' (G1) as students who neither retain nor transfer knowledge, 'nonunderstanders' (G3) as those who can retain knowledge but not transfer it, and 'understanders' (G4) as those who both retain and transfer their knowledge. The missing group, globalizers (G1b), show an 'abnormal response pattern' (Friel & Johnstone, 1988) in which they have difficulty retaining knowledge (KAcc < Mean), but they can transfer it to 'partially familiar' problems. In this study, the G1a and G1b groups were combined to make one group, called "rote learners" because their group centroids could not be adequately resolved, see Prediction of Achievement Group Membership under RESULTS.

Validity and Reliability of Instruments Used

Descriptive Statistics for the Subtests. The overall reliability of this graphical method is shown in Table 2 for six different semesters of general chemistry at two different universities. The statistical characteristics of the two 19-item subtests used in this study are also shown in Table 2 for Chem 101, Fall 1997 semester. Specifically, the mean, standard deviation and range for each of the 19-item subtests were as follows: KAcc subtest: $M = 14.9$, $SD = 3.0$, $R = 6$ to 19, and KCon subtest: $M = 9.7$, $SD = 3.4$, $R = 3$ to 18. The test questions requiring mathematical operations were unevenly distributed between the two subtests: 13 items (68.4 %) were on the KCon subtest, but only 6 items (31.6 %) were on the KAcc subtest. For the two "extra" 4-item question sets on the final examination, the

statistics were as follows-- for Particulate Questions, $M = 1.44$, $SD = 1.06$, $R = 0$ to 4, and for Higher-Order Linking Questions, $M = 1.49$, $SD = 1.09$, $R = 0$ to 4.

Content and Construct Validity of Items Used in Subtests. The validity parameters were established by the chemistry faculty for a large pool of 800 test items. Items used in both subtests of the final examination were randomly drawn-- 1 question from each 20-item module-- for each of the 40 modules. The normal departmental procedure was followed, and no *a priori* effort was made to pre-select any of these items.

Inter-Rater Reliability of Subtests. The reliability of the two subtests with respect to item difficulty was determined by three subject matter experts, who have combined total of over sixty years of college chemistry teaching experience. Informed that the first 40 questions were roughly split at the median in terms of item difficulty, each expert estimated whether each item on the final examination could be classified as "easy" or "difficult" with respect to the median difficulty. The results showed that they were able to correctly classify 80.7 % (15, 15, 16 out of 19) of the nineteen KAcc items as "easy" and 71.9% (13, 13, 15 out of 19) of the nineteen KCon items as "difficult."

State Metacognitive Inventory. The validity and reliability of the SMI has be established and published by O'Neil and Abedi (1996). They reported that the alpha reliability estimates and factor analysis indicated that the metacognitive subscales are reliable (alpha above 0.70) and unidimensional (one factor per subscale). Construct validity of the SMI was acceptable.

Prediction of Achievement Group Membership. The discriminant analysis (DA) statistical program (SPSS, version 8.0) was used for a two-fold purpose: to determine the characteristics of these three achievement groups using multivariate discriminant analysis, MDA, and to predict student membership in each of the three groups using predictive discriminant analysis, PDA. Table 4 shows the eigenvalues and other characteristics of the two canonical functions, F1 and F2, as well as correlations between each of these functions and the discriminating variables that load on each function.

Assessment of Conceptual Understanding. The MANOVA option of GLM (SPSS, v. 8.0) was used to determine the ability of students to answer two extra subtests that appeared at the end of the regular 40-question final examination: (1) a *particulate question set* that consisted of 4 questions that require processing information from sketches of atoms and molecules (Nakhleh & Mitchell, 1993; Robinson, 1996), and (2) a *higher-order linking question set* that required some conceptual knowledge for students to be able to connect two or more sets of information (Wolfe & Heikkinen, 1979). The validity and reliability for each of these instruments was reported in their respective references, cited above.

Perceptions of Achievement Groups. A semi-qualitative research method was used to study differences in the perceptions on learning that students in the different achievement groups used (Table

5). The students in this extension of the main study were all enrolled in two of the six Chem 101 sections used in this study. These two sections were taught by the author, and the pass/fail journal-writing assignments were a small part of the normal course requirements. At the end of the mid-term and near the end of the semester, they wrote two entries on their journal sheets: a "cognitive" entry on what they had learned, and an "affective" entry on how they felt about it. An undergraduate research assistant, who was a college senior majoring in chemistry within the College of Education, evaluated the data without any knowledge of the true intent of this paper and without any knowledge of the students' achievement status within the class. She sorted the students' assignments alphabetically and then used a scoring rubric (see bottom of Table 5) developed by the author to rate each student on the categories listed on the rubric sheet. She then gave the scored rubric sheets to the author who tabulated the points per category for each student. Thus, this evaluation involved the perceptions of the research assistant regarding the perceptions of the students' as recorded on their journal sheets. The results are reported in the RESULTS Section below, and the correlations among these categories and other variables in this study are shown in Table 6.

RESULTS

Graphical Achievement Method

Regression Lines. The results of the application of this method are shown in Figure 1 for the sample of 153 students used in this study. Two regression lines minimized the variance of student scores on the two dimensional graph:

- the *memorize line,* which is the regression line (D-C) for students scoring below the mean (M = 14.9) on the easier KAcc subtest had a shallow slope of +0.37, whereas
- the *conceptual line*, which is the regression line (C-A) for students scoring above the KAcc mean had a steep slope of +1.31.

A plausible explanation for the much greater slope of the *conceptual line* (C-A) is that these students were able to "see connections" between their knowledge fragments (Baxter & Glaser, 1998; Crawford et al., 1998; Raghavan, Sartoris, & Glaser, 1997). A slope of +1.00, by comparison, indicates that if students improved their KAcc score by one question, then they also improved their KCon score by one question despite the fact that the latter set of questions were much more difficult. The more impressive slope of +1.31 indicates that if students acquired the additional knowledge needed to answered 3 more KAcc questions correctly, then they could correctly answer four KCon questions (i.e., 3 * 1.31 = 3.93). This implies that knowledge is being reconstructed (Cizek, 1997; Johnstone, 1997) when students improve their achievement performance along the conceptual line.

In contrast, those students who improve their performance along the *memorize line* (D-C) are apparently acquiring knowledge fragments in relative isolation (Baxter & Glaser, 1998; Raghavan, Sartoris, & Glaser, 1997) because the additional knowledge gained applies mostly to easier KAcc questions rather than to the more difficult KCon questions. The slope of +0.37 means that acquisition of the additional knowledge needed to solve 8 KAcc questions results in only 3 additional KCon questions being correctly answered (i.e., 3/8 = 0.375).

Graphical Achievement Groups

When the KAcc and KCon scores of individual students are plotted on top of Figure 1, (new graph not shown) each of the three achievement distributions is found clustered along one of the three regression line segments. The achievement characteristics of each of these groups are described in the following paragraphs.

Rote learners. These are students who scored below the KAcc mean (G1a and G1b subgroups combined—see *Labels for Achievement Groups*), and their scores tend to cluster along the memorize line (D-C) in Figure 1. Most of them can answer easy one- or two-step problems/ questions that are familiar to them. For example, on Question 19, 80.6 % correctly solved for mass in g when given volume in liters and density in g/mL. However, they have difficulty solving a familiar problem that includes more steps, e.g., on Question 15 only 59.9 % of them correctly solved for % S in $Na_2S_2O_3$. Very few of these students could answer a familiar problem that required the integration of two different sets of data. For example, on Question 40, only 40.0 % of them could correctly calculate molecular formula when given masses in g for each element (to obtain the empirical formula) and then combine with the molecular weight of the compound (to obtain the molecular formula).

Algorithm memorizers. These are students (G3) who scored above the KAcc mean but below the KCon mean ($M = 9.7$). Their scores cluster along the extended memorize line (C-B) in Figure 1. Algorithm memorizers tend to be successful on the more familiar/easier questions that tend to be "straight-forward." For example, on question 15 (% S in $Na_2S_2O_3$), 92 % of these students calculated the correct answer, and on question 19 ($m = D * V$), 85 % obtained the correct answer while 77 % were correct on question 40 (empirical/molecular formulas). However, they tend to have difficulty with a problem that is "less familiar" to them, but one that can be easily solved with a mathematical operation, e.g., ratio and proportion. For example, only 38 % of these algorithm memorizers could solve a dilution problem (question 21) that contained units that were different from those typically used in the "algorithmic equation" ($M_{dil} * V_{dil} = M_{con} * V_{con}$) taught during the semester. By comparison-- 52.5 % of the rote learners correctly answered this question.

Conceptualizers. These students (G4) scored higher than the mean on both the KAcc and KCon subtests. Their scores cluster along the conceptual line (C-A) of Figure 1, which has a steep slope (+1.31). They are very successful on a problem that requires one of two possible approaches: either solve it with two or more successive sub-problems (equations) or use one equation apply complex algebraic manipulations. For example, on question 31, 84 % of them were successful in solving for ΔT (change in temperature) and then solving for final temperature ($T_{fin} = T_{init} + \Delta T$). Conversely, only 46.0 % of the algorithm memorizers and 25.4 % of the rote learners successfully solved this problem. Although these "conceptualizers" were successful in solving the more complex mathematical problems, this success does not necessarily lead to success on conceptual questions, i.e., questions requiring visualization of the behavior of particulates (particles) during physical or chemical processes. This question of "transfer" from a mathematical understanding to a conceptual understanding is discussed in the next subsection.

Assessment of Conceptual Understanding

Many of the questions on the final examination used to classify students into the achievement groups required mathematical operations. Thus, in order to assess students on their conceptual understanding, two independent measures were taken from the "extra questions" on the final examination. On the four-question *particulate problem set*, only 37.0 % of the "conceptualizers" could meet the criterion of correctly answering at least three of the four questions (see Table 7). Furthermore, a similar proportion of student in this group, 44.4 %, meet the criterion on the four *higher-order linking questions*. A more conservative estimate of the proportion of "true conceptualizers" revealed that only 22.2 % met the success criteria on both sets of questions. However, none of the students classified in the other two groups, i.e., algorithm memorizers and rote learners, were successful on both sets. On the particulate questions, only one of the 24 "algorithm memorizers" (4.2 %) was able to meet the criterion, while three of them (12.5 %) were successful on the higher-order linking questions. Similar proportions were found among the rote learners: two out of 52 (3.8 %) meeting the criterion for particulate questions and seven (13.5 %) were successful on the linking question set.

Prediction of Achievement Group Membership

The predictive discriminant analysis (PDA) procedure was used to determine the cognitive and metacognitive characteristics for each of the graphical achievement groups. As shown in Table 8, the PDA procedure was able to correctly predict the classification for 71.8 % of the students in sample used in this study. Specifically, the proportion of each achievement group correctly classified was as follows: 37 of the 52 rote learners (71.2 %), 16 of the 24 algorithm memorizers (67.7 %), and 21 of the 27 conceptualizers (77.8 %). Among the students who were misclassified the number of exchanges between

the rote learners and algorithm memorizers was greater than the exchanges between the rote learners and the conceptualizers. Specifically, four (16.7 %) predicted rote learners were algorithm memorizers, and eleven (21.2 %) predicted algorithm memorizers were rote learners. Also, an even exchange rate occurred between the algorithm memorizers and the conceptualizers. Four (16.7 %) predicted conceptualizers were algorithm memorizers, and five (18.5 %) predicted algorithm memorizers were conceptualizers. Conversely, the rote learner-conceptualizer transitions were relatively rare: four students (7.7 %) predicted to be conceptualizers regressed to the rote learner group, and only one student (3.7 %) progressed from rote learner to conceptualizer classification. These transitions may be significant in terms of students who experienced conceptual change during the semester, see DISCUSSION.

The basis for PDA prediction of achievement group membership consisted of characteristics (discriminant variables) that correlated with one of two primary canonical discriminant functions, F1 and F2. As shown in Table 4, achievement, mathematics confidence, and aptitude variables correlated with F1, whereas metacognitive categories, years of high school chemistry, gender, and pre-chemistry confidence correlated with F2. Two achievement variables-- hour exam average ($r = 0.717$) and chemistry pretest score (CPT, $r = 0.323$)-- showed the highest and third highest correlations with the F1 function, respectively. Aptitudes for mathematics, (ACT-Math, $r = 0.607$) and scientific reasoning (ACT-S R, $r = 0.302$) were also highly correlated with F1. The inclusion of the final F1 variable, mathematics confidence ($r = -0.197$), suggests that the F1 function consisted of a mathematics-related cluster of prior achievement plus aptitudes for mathematics and logical reasoning. In contrast, the F2-loading variables were dominated by the metacognitive categories of the SMI, which was given to students immediately after they took the CPT during the first week of the semester. These F2 categories included planning ($r = 0.529$), self-checking ($r = 0.470$), awareness ($r = 0.209$), and cognitive strategies ($r = 0.201$). Other F2 variables included years of high school chemistry ($r = 0.308$), gender ($r = 0.278$), and pre-chemistry confidence ($r = -0.233$).

The fact that the two variables that gauged *academic self-confidence* correlated with two different functions, F1 and F2, suggests that there may be two different dimensions that contribute to successful achievement in chemistry. The inclusion of *mathematics confidence* with F1variables that depend upon mathematics aptitudes supports the idea that mathematics was the primary function in determining chemistry achievement as measured by the KAcc and KCon subtests of the final examination. On the other hand, the second dimension of chemistry achievement, which includes *pre-chemistry confidence*, seems to be dependent upon metacognitive factors, which showed higher correlations with the KAcc subtest, i.e., planning ($r = 0.336$), self-checking ($r = 0.209$), and awareness ($r = 0.170$)[1].

The "territorial map" (Figure 2) for the PDA predicted achievement group membership shows how the two canonical discriminant functions, F1 and F2, were used to predict and classify these three groups. As shown in Figure 2, the F1 function clearly separates the "conceptualizers" from the "rote learners." Conceptualizers scored significantly higher on all F1 variables than did the rote learners (Table 9). In other words, the F2 function is not needed to separate and then classify student membership between these two groups. Consequently, there were very few "transitions" across the barrier between these two groups. Four students who were predicted to be conceptualizers regressed on the final examination to become rote learners, while one student made the transition from rote learner to conceptualizer. This particular student met the criteria for both of the question sets that queried conceptual understanding. Thus, the use of "think-aloud protocols" to probe this individual's apparent "conceptual change" might have yielded some valuable information about his internal representations and his epistemological commitments[2].

The inclusion of algorithm memorizers on the territorial map (Figure 2) shows that the F1 scores of this group overlap both the scores of rote learners (negative F1 values) and the scores of conceptualizers (positive F1 values). Thus, the F2 discriminant variables provided the sole means of separation between algorithm memorizers and the other two groups. Essentially, these students had positive values on their F2 dimension and mid-range values on the F1 function. When compared to the rote learners on the discriminant variables (Table 9), the algorithm memorizers had significantly higher "hour exam" averages (F1 variable) and higher metacognitive planning and self-checking scores (both F2 variables). However, they had similar ACT-Math scores (F1), while their chemistry pretest scores (F1) overlapped with those of the rote learners on the low end and the conceptualizers on the high end. Thus, it is not surprising that there were a greater number of transitions between algorithm memorizers and rote learners than any other possible transition. This information suggests that the learning modes of these two groups exhibit a significant degree of overlap.

Perceptions of Achievement Groups

The written responses of a sub-sample of students on two journal-writing assignments were assessed in order to ascertain which student perceptions might interact with the KAcc and KCon achievement measures and with the F1 and F2 functions. The results of this additional study (see Table 5) showed a highly significant Chi Square statistic, $p = 0.004$, for anxiety and a tendency towards significance for difficulty level, $p = 0.08$. With regard to the former, only one out of 14 conceptualizers (7.1%) expressed anxiety, whereas many of the algorithm memorizers (7 of the 11, 63.6%) and rote learners (14 of the 25, 56.0%) exhibited anxiety on the written assignments. In addition, most of the

conceptualizers (10 of 14, 71.4%) gave the impression that they felt that the course was relatively "easy" (Level 1), while most of the algorithm memorizers (8 of 11, 72.7%) and rote learners (18 of 25, 72.0%) seemed to view the course as "moderate or difficult" (Levels 2 or 3).

For the most part, several of these preception variables showed significant correlations with both the achievement and aptitude variables used in this study (Table 5). Thus, students in the different achievement groups showed different perceptions possibly due to differences in either their F1 variables or in their F2 variables. For example, conceptualizers may have used their success on the F1 variables to lower their levels of anxiety as illustrated by the fact that only one of 14 expressed anxiety (7.1 %). Also, four of the 14 students in this group (28.6 %) commented in writing about instances in which the connections between class topics and real world applications were made (Level 3). Conversely, all of the algorithm memorizers tended to ignore "unusual teaching methods" (Level 3) while only one out of 11 (9.1 %) mentioned an unusual method used in the classroom (Level 2). Another comparison between these two groups tended to show a reciprocal relationship among students who expressed a learning approach that was higher than the "surface approach" (Level 1). That is, conceptualizers (5 of 14, 35.7%) seemed to prefer a "deep approach" (Level 3) to learning the material, whereas the algorithm memorizers (5 of 11, 45.5%) tended to ignore this approach while favoring the "strategic/ algorithmic approach" (Level 2). Overall, the findings from these perception variables are consistent with the results found on the predictive F1 and F2 variables. Furthermore, the combination of both types of variables suggests qualitatively distinct "achievement scenario" for each of the three achievement groups, as discussed below.

Achievement Scenarios

Conceptualizers' Scenario. The achievement scenario for this group is based upon their possession of a cluster of math- and logic-related aptitudes (higher ACT-Math and ACT-Scientific Reasoning scores) found in the F1 dimension (see Figure 2). This F1 cluster may have been used to both reduce anxiety about the course and to become successful on the hour exam averages-- another F1 variable. Thus, they were well prepared for both subtests of the final examination. That is, they performed well on the easier KAcc subtest, which contained only 6 math-related items, and on the more difficult math-intensive KCon subtest (13 math-related items). In summary, their superior mathematical understanding was possibly based upon their use of both stages of algorithmic understanding, as described earlier in this paper, and possibly some conceptual understanding of the subject matter knowledge in the course.

Two Types of Conceputalizers. When these results are compared and contrasted with those from the subsection on *Assessment of Conceptual Understanding*, it became apparent that only about one-

third of these students may have been able to integrate their mathematical understanding with their conceptual understanding. That is, the majority of conceptualizers, over two-thirds of them, were *not* able to combine these two types of understanding. This chasm within the achievement group labeled "conceptualizers"-- based upon their positive/positive quadrant and illustrated by the clustering of their subtest scores along the conceptual line (C-A in Figure 1)—warranted two new labels for these emerging subgroups. Thus, those students who met the criterion on the particulate question set (correct on ≥ 3 out of 4 items) are re-labeled as 'true conceptualizers' while those who did not attain it are called 'math conceptualizers' due to their characteristics described below.

Success on the particulate question-set provided the criterion variable for their separation: based upon the original group of 34 students, 12 were relabeled as 'true conceptualizers' and 22 as 'math conceptualizers.' A search for significant differences between these two subgroups on all of the independent variables revealed only two differences. Both of these differences favored the 'math conceptualizers':

- who had a higher mean (M = 89.8) on the "hour exam averages" (p = 0.06) than the 'true conceptualizers' (M = 84.7), and
- who, for the most part (13 of 22, 59.1 %), were "very confident" in their ability to apply mathematics to the course material (Chi Square = 3.62, p = 0.06), while only several 'true conceptualizers (3 of 12, 25.0 %) expressed this degree of confidence.

One implication from these results is that the greater math-related prior achievement and degree of math confidence among the 'math conceptualizers' made their chemistry-related conceptions more stable and hence less susceptible to conceptual change. Conversely, the 'true conceptualizers' may have been able to visualize/verbalize their conceptions better and thus to see if a conceptual change in the knowledge structures was needed[3]. Overall, this 'true conceptualizer' group was apparently able to integrate their mathematics and conceptual understandings into a coherent conceptual network of subject matter knowledge.

Algorithm Memorizers' Scenario. On the surface, this group appeared to send an enigmatic message regarding the factors that affected their achievement in the course. That is, they seem to have compensated for their lower mathematics aptitudes (ACT-Math) by the intentional use of metacognitive planning and self-checking to monitor and improve their achievement performances. Specifically, their mean "hour exam average" (M = 81.46, SD = 9.46) was not significantly different from the mean of the conceptualizers (M = 87.58, SD = 9.26). However, their anxiety levels were comparable to those of the rote learners despite their metacognitive adaptations and moderately successful achievement performances during the semester.

A plausible explanation for this enigmatic behavior among the algorithm memorizers would be that they might have been aware of their dependence upon on a single learning strategy, i.e., the algorithmic approach. In fact on the SMI metacognitive post-test[4], algorithm memorizers were significantly less inclined ($p = 0.04$) than the conceptualizers to agree with the statement that they "used multiple thinking techniques or strategies to solve the test questions." In other words, algorithm memorizers may have felt that if their "single strategy" were to fail in any way, then their entire achievement performance would be in jeopardy. This awareness would indeed generate anxiety about the course. Also, they might have been aware that this strategy/method was limited in its scope and that it was not effective in solving the more difficult mathematics and other step-by-step problems on the hour examinations.

The algorithm memorizers' "achievement scenario" focuses upon their metacognitive plan to use primarily an algorithmic learning strategy to solve the step-by-step problems that they apparently perceived to consist of the entire subject matter knowledge in their chemistry course. This learning strategy is superior to that of the rote learners' strategy because they used algorithms to link fragments together. Consequently, they may have used this strategy to work the more familiar problems found on the KAcc subtest. However, they were not able to extend this success to the math-intensive KCon subtest[5]. This algorithmic strategy was extremely limited in its applicability because the KCon subtest contained many more math-related problems (13 of 19) than did the KAcc subtest (6 of 19). Thus, algorithm memorizers may have been using the first stage of algorithm understanding, but apparently they did not extend it to the more demanding second stage for this type of understanding. Their conceptual understanding as measured by the 4-item particulate question set was essentially nil[6], i.e., it approached the random guess level.

Rote Learners' Scenario. In contrast to both the conceptualizers' and algorithm memorizers' scenarios described above, the rote learner group tended to begin the semester with significantly less prior knowledge and with lower mathematics aptitudes. Apparently, these factors may have contributed to the anxiety that many of these students (14 of 25, 56.0% at Level 2) expressed about the difficulty (18 of 25, 72.0% at Levels ≥ 2) they were having with the course. This difficulty was manifested by lower performances on both their "hour exam averages" and on the KAcc and KCon subtests of the final examination. Also, very few of them wrote their assignments at the highest cognitive level (2 of 25, 8.0% at Level 3), rather they were inclined to express cognitive levels in which they listed topics at either the specific level (32.0% at Level 1) or the generic level (60.0% at Level 2). Thus, the "rote learner scenario" begins with lower prior knowledge (CPT scores) and mathematical aptitudes (ACT-Math), which produces anxiety about the difficulty they are having with achievement on hour examinations.

These factors, in turn, induce achievement to spiral into a downward loop that culminates in their mean final examination scores being 16.0 points lower than the mean for their hour exam averages.

DISCUSSION

The three achievement scenarios developed in the last section represent plausible explanations for the achievement, perception, cognitive, and metacognitive variables used in this study. However, in order to guide further research studies that might produce a more generalized and validated construct (Alexander, 2000), these results must be interwoven within the theoretical framework of *domain specific conceptual change models* (DS-CCM) (Vosniadou & Ioannides, 1998). Although the author expected to see results that supported the "strong restructuring" stage of conceptual change, the results more clearly suggest that most of the college students in this sample were either not engaged or were engaged in only the "weak restructuring" stage of conceptual change.

Domain-Specific Conceptual Change Model

The DS-CCM is based upon the application of several prominent conceptual change models that provide a coherent theoretical framework capable of explaining the relationships between the achievement scenarios described in this paper and the set of discriminant variables that distinguished the three achievement groups found in this study. As shown in Figure 3, conceptual change is a complex process that involves the learner's existing conception and its interactions with the instructional message. These interactions are primarily social interactions between the teacher and the student or interactions among students (Linn et al., 2000). Learners with different levels of achievement and thus relative expertise in the domain often exhibit structural differences in their conceptual organization of the domain (Wilson, 1996). During science instruction learners may not be aware of their *ontological beliefs* about a particular phenomenon or concept; however, if they have placed objects and events into inappropriate ontological categories, then they may develop misconceptions (Chi, 1992; Tyson et al., 1997). Likewise, their *epistemological commitments* determine the extent to which they can generalize their knowledge and link knowledge fragments together (Baxter & Glaser, 1998; Raghavan, Sartoris, & Glaser, 1997) to form an internally consistent conception (Hewson, 1996; Tyson et al., 1997).

Achievement Scenarios, Discriminant Variables, and the DS-CCM

Rote Learners, Achievement & the DS-CCM. In terms of DS-CCM framework, the rote learners were not engaged in conceptual change because they seemed to lack the epistemological commitment needed to understand the subject matter and to make learning it a meaningful experience.

That is, they may have been "satisfied" with a learning strategy that focused upon *accretion*-- the accumulation of knowledge fragments (Baxter & Glaser, 1998; Raghavan, Sartoris, & Glaser, 1997). Thus, any attempt by these learners to link their atomistic concepts together into a more meaningful conceptual network of knowledge (Vosniadou & Ioannides, 1998) was probably a frustrating and formidable task. If their ontological beliefs centered upon atoms and molecules as "concrete things" rather than their own developing mental models of abstract entities, then no conceptual change was possible (Chi, 1992; Vosniadou, 1994). Furthermore, these 'inappropriate' beliefs (Spada, 1994) probably reduced the course content to that of an "applied course in mathematics." As compared to the mathematics aptitude of conceptualizers, rote learners had significantly lower ACT-Math scores, which made the math-intensive final examination very difficult for them. Thus, they may have found themselves struggling merely to accumulate knowledge without any algorithmic or conceptual understanding of the subject matter.

Algorithm Memorizers, Achievement, & the DS-CCM. In contrast with the above achievement scenario and DS-CCM framework, the algorithm memorizers made a metacognitive plan at the beginning of the semester, which they monitored (self-checking subscale) in order to compensate for their lower mathematics aptitude scores (ACT-Math). This algorithmic approach probably originated in their prior learning experiences while being reinforced by the instructional method (Case & Fraser, 1999) used in the course. By focus on algorithmic strategies, they were "fine tuning" their conceptual structures (Rumelhart & Norman, 1978) in an attempt to assimilate procedural knowledge. Thus, they were apparently engaged in a weak conceptual change strategy that improved their subject matter knowledge (Mayer, 1998), but one that ignored their underlying fundamental conceptual deficiencies (Case & Fraser, 1999). Their epistemological commitment seemed to be to "imitate" the knowledge of subject matter experts by internalizing "larger chunks" of knowledge. This commitment allowed them to automatize their information processing, which is one of the attributes of intelligence (Sternberg, 1998). However, this knowledge was inflexible because it stemmed from their lack of metaconceptual awareness (Vosniadou, 1994; Vosniadou & Ioannides, 1998), which prevented them from questioning their prior knowledge (Case & Fraser, 1999) and encouraged only the assimilation of new information into existing conceptual structures (Spada, 1994). Nonetheless, they seemed to be able to use their metacognitive planning and self-checking strategies (O'Neil & Abedi, 1996) to extend the memorize line (segment C-B in Figure 1) up to its "dead end" (point B in Figure 1). Overall, their "learning mode" was still one of "memorization" as indicated by the large number of similarities (F1 and perception variables) they shared with the rote learners' characteristics.

Conceptualizers, Achievement & the DS-CCM. The 'true conceptualizers,' about one-third of the members of this group, were able to integrate their mathematical understanding, which was

augmented by the F1 variables, with their conceptual understanding. Thus, they experienced a relatively high level of engagement with the subject matter knowledge, which allowed them to acquire either a strong conceptual change or in some cases no conceptual change (Dole & Sinatra, 1998). Their ontological beliefs may have served as a lens (Tyson et al., 1997) through which they could change their beliefs to ones that agreed with more scientifically correct conceptions. For example from the conception that atoms and molecules are "concrete things" to one in which they constructed a mental model that was based upon empirical evidence, e.g., Rutherford's gold foil experiment and the nuclear atomic model.

Apparently, these students expressed less anxiety about their difficulty in learning the subject matter knowledge because any new conception contributed to a more coherent network of conceptual knowledge (Wilson, 1996). Thus, they may have been motivated to make a greater epistemological commitment to understanding chemistry. This commitment, plus appropriate visual imagery of conceptions (Willoughby et al., 1997), may have allowed them to construct knowledge during the final examination on the KCon subtest items that they initially perceived as being only "partially familiar." The steep slope (+1.31) of the conceptual line (C-A in Figure 1) provides evidence to support this supposition. Although this high level of engagement may have separated their existing conception from a dependence on the instructional message (movement to the left in Figure 3), it may have enhanced their intrinsic motivation for the subject (Mayer, 1998) and lowered their anxiety level. These features of the 'true conceptualizer' version of the DS-CCM may have generated a positive feedback cycle that galvanized variables found in their superior F1 mathematical aptitudes/achievements/confidence with their positive set of perceptions (Entwistle, 1994).

Instructional Interventions.

In this study the instructional strategies that the chemistry instructors used to teach their lecture sections were constricted by several factors[7]:

1. the vast amount of content material covered in the course, i.e., ~ 500 pages, 13 chapters, ~150 vocabulary words, ~1000 assigned problems;
2. the lack of a discussion session or a laboratory component; and
3. the lack of adequate prior knowledge of chemistry and the requisite need for mathematics.

These constrictions, and their interactions with one another, may have been largely responsible for the low levels of engagement that many of the students in this study experienced during the course.

Vosniadou and Ioannides (1998) have suggested a rationale' for developing instructional interventions that are designed to make students aware of their implicit representations, and to provide meaningful experiences in order to motivate learners to understand the limitations of their explanations.

They recommend learning environments that allow students to increase their metaconceptual awareness during group discussions by expressing their internal representations and beliefs. Specifically, they state that technology-supported learning environments can be constructed to help students express their internal representations of phenomena and to compare them to those of other learners. This internalization process should be supported by scaffolding-- an instructional strategy that can be used to balance intellectual challenge with a system of temporary supports (Roehler & Cantlon, 1997). In addition, the instructional design of these environments should take into consideration the limits imposed by memory capacities (Sweller et al., 1998) and reasoning chains (Johnston et al., 1997) of learners. Mayer and his coworkers (Mayer, 1997; Moreno & Mayer, 1999) have used multimedia learning to overcome these limits and allow students to actively select, organize, and integrate verbal and visual information. This integration is essential for novices to be able to develop both a mathematical and a conceptual understanding of chemistry (Kleinman et al., 1987; Mathewson, 1999).

The findings in this study suggest that different types of learners may need different instructional interventions in order to optimize their learning experiences. For example, a computer-based simulation (C-BS) can be designed to provide either a prescribed or an exploratory instructional pathway/ environment (Landa, 1976; Suits & Lagowski, 1994; Windschitl & Andre, 1998). Windschitl and Andre (1998) found an interaction between students' epistemological beliefs and C-BS instructional environment in a college-level biology class (N = 250). Students who held more sophisticated beliefs achieved better with an exploratory pathway, while those who were less sophisticated did better in the more prescribed, confirmatory C-BS environment. In terms of the DS-CCM (Figure 3), the former may have been able to apply their epistemological commitments to the exploratory pathway in such a way as to increase their level of engagement with the learning task. Conversely, the latter group may have used the prescribed pathway to maintain a lower level of engagement, whereas they may have been 'disengaged' by the exploratory pathway.

In a college-level general chemistry course, Suits and Lagowski (1994) also found an interaction between student characteristics, i.e., gender and reasoning level, and C-BS instructional pathway. In the pilot study, students (N = 254) experienced a less-structured exploratory pathway on six C-BS units. On the final examination, males achieved higher than females and formal-operational reasoners outperformed transitional reasoners who, in turn, outperformed concrete-operational reasoners. For the main study, the C-BS instructional environment was revised; i.e., each unit was given a more explicit structure, which included scaffolding strategies (Guzdial, 1994) to support the inquiry process. On the final examination, the main effects were diminished, but an interaction effect was found between gender and reasoning level. Among these students (N = 380), males achieved higher than females on the lower cognitive subtest. However, females tended to outperform males on both the middle- and higher-cognitive subtests because

transitional and formal-operational females outperformed males. Thus, the more-structured C-BS environment may have provided conceptual guidance (Chin & Brown, 2000) that fostered greater female problem-solving achievement, but it may have inhibited male achievement. In terms of the current study, it could be that females were able to use the more structured C-BS environment to make the transition from algorithm memorizer to conceptualizer. If this supposition is valid, then the gender gap in science achievement could be due, in part, to the traditional instructional practices used in the physical sciences.

Suits and Courville (1999) designed and used a multimedia learning module expressly for small groups of students who interact with the technology and with each other. Students work as a team to solve a problem that involves real-world applications of the gas laws (automobile air bag inflation). This interactive task stimulates student interest and elicits their internal representations, while giving them immediate feedback in terms of the chemical and physical consequences that result from their proposed solutions. For example, if they calculate an amount of sodium azide that is too small, then they actually *see* the air bag under-inflate and *hear* the expanding air inside it. These experiences should help learners perceive the subject matter knowledge as being more personally relevant (Dole & Sinatra, 1998), which might result in an integration of their interests, prior knowledge, and learning strategies (Tobias, 1994).

Recently, Marcia Linn and her colleagues (Linn et al., 2000) have compiled a set of coherent science activity structures that they found in their study of Japanese late-elementary school science instruction. Each lesson begins with an activity designed to connect it to student interest and prior knowledge, then continues with investigations that follow the guidelines of scientific methodology until the last activity, in which students are asked what they would like to investigate in their next lesson. This coherent inquiry process featured frequent student-student and student-teacher interactions that reflect a deep approach in learning to link together scientific phenomena and principles. Apparently, this type of instructional intervention could result in students experiencing a high-level of engagement that should result in "strong conceptual change." If this type of pre-college and college science instruction were to become widespread, then the domain specific conceptual change model (DS-CCM) could study "true conceptualizers" as the norm rather than as a rarity—as was found in this study.

ACKNOWLEDGEMENTS

The author gratefully acknowledges the intellectual contributions of and support from many scholars. Joe Lagowski and Conrad Hinckley, working in tandem, have supported this work extensively. I appreciate the advise from and efforts of Russ Ham, Joe Sneddon, Linda Brannon, Ken Koedinger, Harry O'Neil, Bill Robinson, Merl Wittrock, three anonymous SMK-CC reviewers, and last but not least Marcey Broussard. Also, the financial support given by the Chavanne-Miller Endowed Professorship in Science is acknowledged and appreciated.

NOTES

Note 1: It appears that the success of the algorithm memorizers on the KAcc subtest may be related to their relatively high scores on this F2 function. If this correlation is valid, then some form of "weak conceptual change" may be occurring within this group of students.

Note 2: Although we did conduct several "think-aloud protocol" interviews with Chem 101 students as they solved chemistry problems, we have no recorded interviews. Unfortunately, the audio tapes were somehow lost in/ or removed from/ the author's research laboratory. The author, and his undergraduate and graduate research assistants were unable to locate the missing tapes.

Note 3: Two members of this 'true conceptualizer' group overcame adverse factors: One student had to overcome low ACT-Math (15) and ACT-Scientific Reasoning (13) scores and a complete lack of confidence in his pre-chemistry abilities. Another student apparently used a high ACT-Math score (26) plus some other unknown factor to compensate for a very low hour exam average (61.5). Conversely, a third 'true conceptualizer' had very high ACT-Math (32) and ACT-Scientific Reasoning (35) scores plus she turned down an academic scholarship to a prestigious Ivy League university. For personal reasons she elected to attend the 'less prestigious,' regional university in Louisiana at which this study was conducted. The Ivy League school may have its water-propelled racing-shell crew, but we have our motor-propelled plastic bead-throwing krewe during Mardi Gras festivals.

Note 4: As described in the METHOD section, students responded to the SMI metacognitive questions after taking the CPT pretest during the first week of the semester. However, they also took the SMI as a "post-test" immediately after taking the final examination at the end of the semester.

Note 5: The performance of algorithm memorizers on the easier KAcc subtest (M = 17.1) was comparable to that of the conceptualizers (M = 17.6) and was much higher than that of the rote learners (M = 12.5). Conversely, on the KCon subtest, their mean (M = 9.0) was comparable to the rote learners' mean (M = 7.7) but was much lower than the conceptualizers' mean (M = 14.3).

Note 6: The algorithm meorizers' mean (M = 1.2) on the 4-question particulate question set was comparable to that of the rote learners' (M = 1.3) and was far short of the conceptualizers' mean (M = 2.1). That is, algorithm memorizers were essentially guessing at these questions and the criterion for competency on this set (M = 3.0).

Note 7: In regard to factor (1), modern college general chemistry textbooks contain approximately twice as much material as the corresponding texts did in the 1940's and 1950's. If one considers that each "vocabulary word" is actually a chemical concept, then ten new concepts must be introduced during each week of instruction (150 words/15 weeks). Obviously, all of these concepts cannot be covered in adequate depth for students to really

understand them and to link them together into a conceptual network of knowledge. This "information overload" could overwhelm "short-term memory" and force students to seek an approach that relies upon memorizing the material. This overload situation is confounded by the fact that students entering the course, by most accounts, are less well prepared for it than they were in past decades, factor (3). For example, many high school chemistry teachers attempt to teach the same abstract material that is taught at the college level while tending to shun laboratory work in their courses. They often have good intentions and want to help students learn, but institutional factors often interfere with these idealized intentions. Likewise, at our university we intended to schedule "recitation sessions" for the Chem 101 course; however, budgetary constraints and limited numbers of faculty and staff have made this "good intention" impossible to implement into the curriculum, factor (2).

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Table 1

Two Problem-Solving Achievement Dimensions

Type of operation:	Learner's Perception: Familiar Problem	Partially Familiar Problem	Unfamiliar Problem*
Simple operations	1 or 2 step algorithm (e.g. temperature conversions)	Conceptual puzzle (e.g. given a list of ionic & covalent compounds, rank them based on relative melting point)	Information search (e.g. perform a systematic search for "buckyballs" and "abacus" on the internet)
Complex operations	Multi-step algorithm (e.g. balancing an oxidation/reduction chemical equation)	Conceptual challenge (e.g. given gas law data and a list of chemical names for gases, identify the gas)	Scientific inquiry (e.g. determine the chemical composition of a mineral sample)

* Unfamiliar problems were excluded from this study because their solution often involves resources (e.g., reference materials, research laboratories, etc.) that are not available when students are taking pencil-and-paper tests.

Table 2

Summary Statistics for the Two-Dimensional Model of Chemistry Achievement[a]

Course, Term	*N*	Knowledge Accumulation *Mean*	(%)	Knowledge Construction *Mean*	(%)	Ratio of Means
Chem 222A, Fall 1993	311	15.7	(62.8)	10.0	(40.0)	0.636
Chem 222A, Fall 1994	191	22.6	(68.5)	13.8	(41.8)	0.611
Chem 222A, Spring 1995	85	17.8	(74.2)	10.3	(42.9)	0.577
Chem 101, Spring 1996	113	18.6	(71.5)	10.9	(41.9)	0.586
Chem 101, Fall 1996	175	14.5	(76.3)	8.9	(46.8)	0.614
Chem 101, Fall 1997	153	14.9	(78.4)	9.7	(51.1)	0.651
Overall M (%)	171.9	17.3	(72.0)	10.6	(44.1)	0.612
S D	80.7	3.0		1.7		0.028

[a] All test used to construct this table were comprehensive final examinations that were given in first semester general chemistry courses (Chem 222A or 101) at two different universities.

Table 3
The Graphical Achievement Method

1. Enter data from the examination on a spreadsheet and code student response to each question (Q) as 1 if correct or 0 if incorrect:
   - each row contains data for one student (name, test score, and response to each Q);
   - each column contains the responses of all students to that Q.
2. Perform the following data manipulations in order to produce descriptive statistics:
   - Insert the test score (sum of responses) for each student in a new column, and insert the *M* for each question at the bottom of the spreadsheet.
   - Sort students in rows from highest test score to lowest, and sort the Qs in columns from easiest on the left to most difficult on the right.
   - Calculate item discrimination for each Q;
   - Examine the most difficult Qs & discard any Q that is too difficult &/or nondiscriminating to obtain an even number of Qs retained.
3. Generate two subtests:
   - Divide the test at the median Q (in terms of item difficult) such that each subtest contains the same number of Qs;
   - Calculate the score on each subtest for each student;
   - Label each subtest as follows-- "knowledge accumulation" (KAcc) = easier subtest, and
     "knowledge construction" (KCon) = more difficult subtest;
   - Calculate the class mean (*M*) for each subtest & the "ratio of means" (KCon M ÷ KAcc M);
   - Re-sort students from highest to lowest KAcc score, & calculate Kcon mean for each KAcc;
   - Graph KAcc score (x-axis) versus Kcon mean (y-axis), and draw regression lines as appropriate to minimize residuals (e.g., see Figure 1).
4. Regroup students based on their "achievement quadrants," and then calculate statistics, and correlations with other characteristics
   - Assign "achievement quadrant" *labels* to students as follows:

• if their KAcc score ≥ the KAcc mean--	*Conceptualizer*	(+/+)	if KCon score ≥ (KAcc score x "ratio of means")
	Algorithm Memorizer	(+/-)	if KCon score < (KAcc score x "ratio of means")
• if their KAcc score < the KAcc mean--	*Globalizer*	(-/+)	if KCon score ≥ (KAcc score x "ratio of means")
	Rote Memorizer	(-/-)	if KCon score < (KAcc score x "ratio of means")

Table 4

F1/F2 Canonical Discriminant Functions: Their Characteristics and Correlations With Discriminating Variables

Characteristics:	F1, Canonical Function 1	F2, Canonical Function 2
Eigenvalue	0.961	0.263
% of Variance	78.5 %	21.5 %
Canonical Correlation	0.700	0.456
Wilks' Lambda (F1 & F2)	0.404 (p = 0.000)	
Wilks' Lambda (F2)		0.792 (p = 0.024)
Discriminating Variables:	**F1 Correlation**	**F2 Correlation**
Hour Exam Average	0.717	
ACT-Math	0.607	
Chemistry Pretest Score	0.323	
ACT-Scientific Reasoning	0.302	
Mathematics Confidence	-0.197 *	
Metacognitive Planning		0.529
Metacognitive Self-Checking		0.470
High School Chemistry		0.308
Gender		0.278
Pre-Chemistry Confidence		-0.233 *
Metacognitive Awareness		0.209
Metacognitive Cognitive Strategies		0.201

* Higher values on these two variables are associated with lower levels of students' confidence in their mathematics or chemistry abilities during the first week of the semester.

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Table 5

Distribution of Students (N = 50) in Different Achievement Groups on Variables Used to Assess Their Written Responses on Journal-Writing Assignments

	Cognitive Level			Difficulty Level		Anxiety Level		Learning Approach			Views of Teaching Method		
Level:	1:	2:	≥ 3:	1:	≥ 2:	1:	2:	1:	2:	3:	0:	1:	2:
Conceptualizers *n* = 19	3	5	6	10	4	13	1	8	1	5	9	1	4
Algorithm Memorizers	3	7	1	3	8	4	7	5	5	1	10	1	0
Rote Learners	8	15	2	7	18	11	14	19	3	3	23	0	2
All students:	14	27	9	20	30	28	22	32	9	9	42	2	6
Chi Square:	0.50	*		5.13		10.9		3.48	**		N/A	***	
p =	*0.78*			*0.08*		*0.004*		*0.18*					

Level 0: Method not mentioned

Level 1: Lists specific topics; Easy; No anxiety; Surface approach; Unusual in-class method, e.g., lecture demonstration

Level 2: Lists generic topics; Moderate or Difficult; Anxiety expressed; Strategic/ algorithmic approach; Unusual example noted, e.g., real world application cited

Level ≥ 3: Summarizes/connects topics; Deep approach

* Cognitive Levels 2 and ≥3 combined due to low cell count on Level ≥3

** Learning Approach Levels 2 & 3 combined due to low cell counts

*** No Chi Square test possible due to low cell counts for Levels 1 & 2

Table 6

Correlations Between Perception Variables[a] and Cognitive Variables

Perception Variables:	Cognitive Level	Difficulty Level	Anxiety Level	Learning Approach	View of Teaching Method	Affect	Confidence Level
Cognitive Level	*	-0.118	-0.105	0.388 **	0.255	0.125	0.169
Difficulty Level		*	0.678 ***	-0.144	0.142	-0.185	-0.481 ***
Anxiety Level			*	-0.073	0.120	-0.169	-0.211
Learning Approach				*	0.072	0.250	0.290 *
View of Teaching Method					*	-0.183	-0.206
Affect						*	0.780 ***
Confidence Level							*
Cognitive Variables:							
Knowledge Accumulation	0.168	-0.223	-0.318 **	0.263 *	0.297 *	0.361 **	0.235
Knowledge Construction	0.245	-0.328 **	-0.367 **	0.251 *	0.384 **	0.255 *	0.280 *
Particle Questions	0.333 **	-0.210	-0.298 *	0.122	0.295 *	-0.234	0.055
Linking Questions	0.312 *	-0.290 *	-0.367 **	0.246	0.454 ***	0.069	-0.051
ACT-Math Score	0.163	-0.135	-0.300 *	0.253 *	0.328 **	0.274 *	0.318 *
Chemistry Pretest	0.131	-0.273 *	-0.396 **	0.072	0.206	0.085	0.248

[a] Used to assess student responses on journal- writing assignments

* Significant @ p = 0.05 ** Significant @ p = 0.01 *** Significant @ p = 0.001

Table 7

Distribution of Students in Each Achievement Group Who Demonstrated Competency on Two Sets[a] of Final Exam Questions that Probe Conceptual Understanding.

	Particulate Questions		Linking Questions		Both Types of Questions	
	Incompetent	Competent	Incompetent	Competent	Incompetent	Competent
Conceptualizers	17	10 (37.0 %)	15	12 (44.4 %)	21	6 (22.2 %)
Algorithm Memorizers	23	1 (4.2 %)	21	3 (12.5 %)	24	0 (0 %)
Rote Learners	50	2 (3.8 %)	45	7 (13.5 %)	52	0 (0 %)
All Students	90	13 (12.6 %)	81	22 (21.3 %)	97	6 (5.8 %)

[a] Particulate questions were taken from Robinson (1996), and linking questions were taken from a test of higher order cognitive skills (Wolfe & Heikkinen, 1978). Both sets of questions appeared at the end of the final examination used in this study.

Table 8

Classification Results for the Achievement Groups based on the Predictive Discriminant Analysis (PDA) Procedure[a]

		PDA Predicted Group:		
Achievement Group:	*n*	G1	G3	G4
G4, Conceptualizers	27	1 (3.7 %)	5 (18.5 %)	21 (77.8%)
G3, Algorithm Memorizers	24	4 (16.7 %)	16 (67.7 %)	4 (16.7 %)
G1, Rote Learners [b]	52	37 (71.2 %)	11 (21.2 %)	4 (7.7%)
All students	103	42	32	29

[a] Overall prediction accuracy: 71.8 % (SPSS, version 8.0)

[b] G1 represents two initial subgroups (G1a and G1b) that were combined because PDA indicated no significant difference between their group centroids.

Table 9

Means for the Three Achievement Groups on Variables that Produced Overall Significant F-ratios[a] for the Wilks' Lambda statistic.

Achievement Group:	*n*	Chemistry Pretest	ACT-Math	ACT-Scientific Reasoning	Hour Exam Average	Metacognitive Planning	Metacognitive Self-Checking
		[b]					
G4, Conceptualizers	27	11.81 A	26.07 A	24.78 A	87.58 A	15.22 A B	13.70 B
G3, Algorithm Memorizers	24	10.54 A B	21.96 B	22.83 A B	81.46 A	16.67 A	15.33 A
G1, Rote Learners	52	9.63 B	20.19 B	21.52 B	71.17 B	14.31 B	13.67 B
All students, *M (SD)*	103	10.42 (3.01)	22.15 (4.72)	22.68 (4.76)	77.89 (12.36)	15.10 (3.05)	14.07 (2.94)
F (2, 100) =		5.06	18.63	4.46	24.97	5.36	3.02
p =		*0.008*	*0.000*	*0.01*	*0.000*	*0.006*	*0.05*
Primary canonical discriminant fuction:		F1	F1	F1	F1	F2	F2
Correlation with primary function:		0.323	0.607	0.302	0.717	0.529	0.470

[a] Means for variables that did not produce significant F-ratios are not shown here. These non-significant variables are as follows: the other metacognitive subtests (awareness and cognitive strategy), classification, gender, major, high school chemistry courses (years taken and when taken), prior college chemistry courses, number of high school math courses, and pre-test confidence in math and chemistry skills.

[b] For each variable, means which have the same letter are not significantly different at the $p = 0.05$ level.

Figure 1: Two stages of learning (regression lines) are plotted on a knowledge accumulation versus knowledge construction graph for the comprehensive final examination in Chem 101, Fall 1997, N = 153

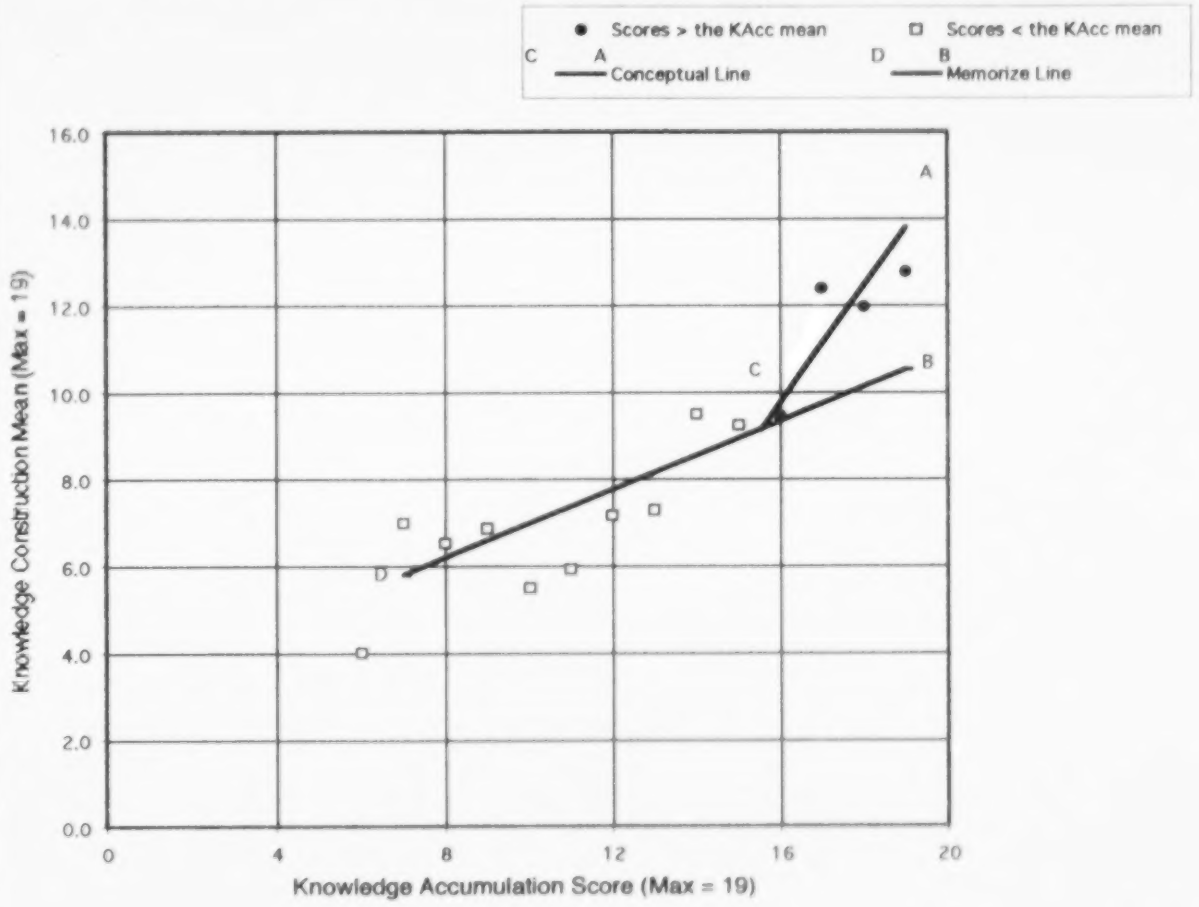

Figure 2.

Figure 2. MDA canonical discriminant fuctions F1 and F2 were used to correctly predict achievement groups for 71.8 % of students (N = 103); arrows show transitions of misclassifed students

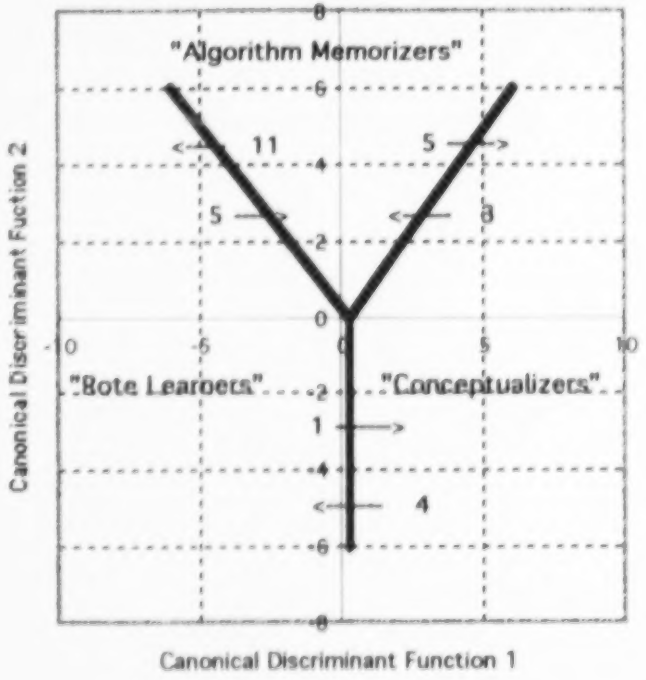

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Figure 3. Domain-Specific Conceptual Change Model (Adapted from Dole & Sinatra, 1998; Tyson et al., 1997)